Retinex Based Flicker-Free Low-Light Video Enhancement

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Abstract. Videos captured in low light environment tend to be poor visual effect. To get better visual experience, a video enhancement algorithm based on improved center-surrounded Retinex and optical flow is proposed in this paper, which contains intra-frame brightness enhancement and inter-frame brightness continuity. In intra-frame brightness enhancement, reflection of each frame is estimated by adjusting the illumination using a weight factor, so that bright illumination is compressed to obtain a reflection with approximately uniform illumination. Then logarithmic image processing subtraction (LIPS) is adopted to enhance its contrast. To maintain inter-frame brightness continuity, the background and brightness changes of adjacent frames are measured using optical flow and just noticeable difference (JND) threshold, respectively. If the background and average brightness change little, their reflection brightness is almost the same, so LIPS parameter of previous frame is applied to current frame. Otherwise, current frame will be updated by calculating its own parameter. Experimental results demonstrate that proposed algorithm performs well in brightness continuity and detail enhancement.

Keywords: Video enhancement · Retinex · Logarithmic image processing subtraction (LIPS) · Brightness continuity

1 Introduction

Affected by the environment, equipment and human factors, images/videos are often of low quality, which significantly reduces the performance of some application fields such as remote sensing image, biomedical image, surveillance video, computer vision. In order to obtain images/videos with better visual effects, various enhancement technologies have emerged. From the aspects of brightness, contrast, color fidelity and naturalness, researchers at home and abroad have made countless contributions to the study of image/video enhancement.

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Over the past decades, many algorithms based on image histogram or Retinex theory have been proposed. Histogram equalization is an efficient way to stretch contrast, but it is prone to over enhancement. To solve this problem, Chen [2] divides image histogram into several ranges, and perform histogram equalization in the separated histogram. Stark [3] performs histogram equalization by clipping image histogram and interpolating cumulative distribution function (CDF) of blocks. However, the extremely narrow histogram of dark areas spreads out too much would result in over-saturation in bright areas. To improve the problem, optimization-based histogram equalization is proposed in [4].

Center-surrounded Retinex algorithms aim to separate the illumination component from input image, and then perform logarithmic transformation to enhance the dynamic range of reflectance component [5–7]. However, estimating illumination with low-pass filter usually generates halo near edges, and enhanced image tends to disturb color information due to the independent process in each color channel. Hence, various improved algorithms have been put forward.

Kimmel [8] first proposes a variation-based method, estimating illumination by solving a quadratic programming optimal problem. Besides, Li [9] proposes an algorithm by introducing a noise term and a gradient term in variational model, so that structure is maintained while noise suppression. Nevertheless, variation Retinex methods usually have high computational complexity. Thus, some scholars prefer to estimate illumination with a filter to acquire enhancements more effectively. Xu [10] proposes perceptual contrast enhancement with adaptive luminance estimation, which uses different filter parameters at different contrast edges. Moreover, Wang [12] presents a naturalness preserved method using priori multi-layer lightness statistics, and gains quite excellent enhancements.

Different from single image enhancement, video enhancement needs to consider the continuity between adjacent frames. Dong [13] enhances video by applying an optimized de-haze algorithm on the inverted video and expediting the calculation of key parameter utilizing temporal correlations between subsequent frames. Huang [14] applies adaptive gamma correction with weighting distribution (AGCWD) to low-illumination video, which uses same gamma mapping curve for similar scenes. Ko [15] enhances video brightness by accumulating similar blocks in adjacent frames. To reduce color distortion and avoid artifacts, they improve color assignment and fuse image using the guide map in [16].

However, Retinex based enhancement algorithms are rarely applied to video, and it is easy to generate brightness flicker when each frame is enhanced independently, because the correlation between adjacent frames is not taken into consideration. To solve this problem, this paper proposes a flicker-free video enhancement algorithm. Main contributions are as follows:

(i) A video enhancement framework based on Retinex is proposed, which consists of two parts: intra-frame brightness enhancement and inter-frame brightness continuity maintenance. Improved center-surrounded Retinex is used to estimate the reflection component of each frame, and its brightness is enhanced by logarithmic image processing subtraction (LIPS).

(*ii*) A method to maintain brightness continuity is proposed, which is to determine the LIPS parameter of each frame according to background and brightness change. Same parameter is taken for adjacent frames with little change of background and brightness because their reflection brightness is similar. Otherwise, parameter is updated. Where background and brightness changes are measured using optical flow and just noticeable difference (JND) threshold, respectively.

The remainder of this paper is organized as follows. Related theories adopted in the proposed algorithm are introduced in Sect. 2. The proposed method is described in detail in Sect. 3. Experimental results and performance comparison are presented in Sect. 4. At last, conclusions are drawn in Sect. 5.

2 Related Works

2.1 Center-Surrounded Retinex Based Enhancement Method

Retinex theory is first proposed by Land [17], which holds that image S we see is the product of illuminance component L and reflection component R.

$$S = L \times R \tag{1}$$

Since the real scene illumination cannot be measured, L is always obtained by estimation. Single-Scale Retinex (SSR) [5], based on the assumption that illumination changes slowly, estimates illumination with Gaussian filter. To preserve information at different scales, Rahman proposes Multi-Scale Retinex (MSR) [6] that weights the reflection components of different scales (Eq. (2)). N takes 3, ω_n and σ_n are the weight and scale parameter. Where ω_n generally takes $\frac{1}{3}$.

$$\log R\left(x,y\right) = \sum_{n=1}^{N} \omega_n \left\{\log S\left(x,y\right) - \log\left[F_{\sigma_n}\left(x,y\right) * S\left(x,y\right)\right]\right\} \tag{2}$$

However, it is pathological to solve the problem based on Retinex model. And the inaccuracy of illumination estimation often leads to halo, noise amplification and color distortion. To improve the visibility of enhanced image, Li [9] and Guo [18] adjust the illumination with global gamma correction, and the enhanced result E is expressed as (3) rather than only reflection component R in (2).

$$E = L^{\gamma} \times R \tag{3}$$

Equation (3) adjusts the illuminance component in real domain, while Xu [10] adjusts illumination adaptively in logarithmic domain with control factor to suppress noise. Our previous work [1] also adjusts illumination with adaptive factor, but uses bilateral filter instead of gaussian to estimate illumination, which ensures the edge details while making the illumination as smooth as possible.

2.2 Optical Flow

Optical flow is defined as the apparent motion in an image sequence, that is, the object motion on image plane can be detected with it. The basic principle of optical flow detection for moving objects is that a velocity vector is assigned to each pixel in the image to form a motion field. Since objects generally move in a relatively continuous manner in space, the image projected onto a two-dimensional plane should change continuously. If the pixel (x, y) in a video frame at time t is $I(x, y, t)$, the optical flow $w = (u, v)$ with horizontal $u(x, y)$ and vertical $v(x, y)$ moving components at that point are

$$u(x, y) = \frac{dx}{dt}, v(x, y) = \frac{dy}{dt} \tag{4}$$

Thus, the constraint equation of optical flow can be expressed as

$$-\frac{\partial I}{\partial t} = \frac{\partial I}{\partial x} \cdot u + \frac{\partial I}{\partial y} \cdot v \tag{5}$$

In order to determine the solution (u, v), extra constraints must be attached to (5). Lucas-Kanade (LK) optical flow proposed by Lucas [19] introduces a local smoothness constraint, assuming that the motion vector is constant over a small space, which is mainly used to calculate sparse optical flow field.

3 Proposed Method

3.1 Algorithm Introduction

To enhance low-light video without brightness flicker, this paper proposes an algorithm based on improved center-surrounded Retinex and optical flow. Algorithm framework is illustrated in Fig. 1. For each incoming frame, improved center-surrounded Retinex is used to estimate its reflection. If the incoming frame is the first frame of a scene, its reflection brightness is enhanced with LIPS by calculating parameter adaptively. Otherwise, the background change is judged by counting the proportion of motion pixels in background. If there is no change, then determine whether the scene brightness mutation. If not, the LIPS parameter of previous frame is used to enhance current frame. As long as the background or average brightness change significantly, LIPS parameter and first frame number of the new scene are updated. Where the background is estimated with P-frames before current frame using optical flow.

3.2 Intra-frame Brightness Enhancement

This paper proposes a bright illumination adjustment and reflection contrast enhancement method to enhance each frame. The processing is performed on V channel without affecting hue (H) and saturation (S). Based on center-surrounded Retinex, adaptive weight factor is used to adjust illumination estimated by bilateral filter. And the contrast of reflection is enhanced with LIPS.

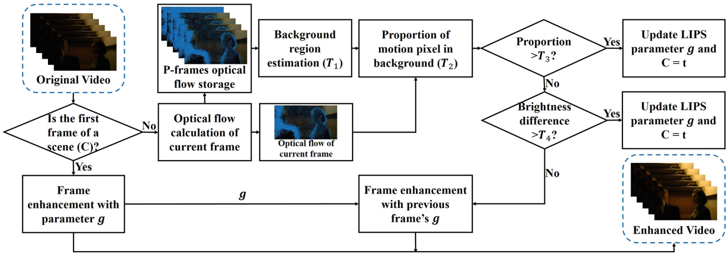


Fig. 1. Framework of video enhancement algorithm.

Bright Illumination Adjustment. Videos acquired at night are often of uneven illumination due to complex lighting. So it is necessary to adjust the illumination image to make it nearly uniform for enhancement. This paper adds a weight factor to adjust illumination in the logarithmic domain, which is defined in (6). Where V is the brightness of original frame and R' is the estimated reflection component. Bilateral filter is selected as $F_{\sigma_n}(x, y)$ in this paper.

$$\log R'(x, y) = \sum_{n=1}^{N} \omega_n \left\{ \log V(x, y) - \beta \cdot \log \left[F_{\sigma_n}(x, y) * V(x, y) \right] \right\} \tag{6}$$

Aimed to eliminate halo, adaptive scale parameters are adopted in [10]. Inspired by it, brightness standard deviation of bilateral filter is locally set. Edge position is detected by *Canny* operator, and parameter σ_n at weak contrast edge is large, while a little smaller one $0.6\sigma_n$ at high edge. In addition, the average of three scale filtered images is used as background illumination.

By converting (6) to the real domain (Eq. (7)), we find that adjusting illumination with β in logarithmic domain is similar to $1-\beta$ correcting illumination in real domain. Image enhancement with globally fixed β improves the brightness but contrast is insufficient. Obviously, adaptive β is better. To obtain a approximately uniform illumination, $1-\beta$ decreasing with illumination is needed to improve the brightness in low-illumination area (lower than 127), while gradually increasing $1-\beta$ is for bright-illumination region (larger than 127). That is β first increases and then decreases, with 127 as the turning point.

$$R' = e^{logV - \beta logL} = \frac{V}{L^{\beta}} = \frac{L \cdot R}{L^{\beta}} = L^{1-\beta} \cdot R \tag{7}$$

From the just noticeable difference (JND) [23] defined in Eq. (8), we find that it is negatively correlated with the value of β. Taking into account the naturalness and contrast of frames, the adaptive β is set in conjunction with the JND threshold. In Eq. (9), q controls the floating range of β, p determines the starting position of β, and l is the background luminance. The larger the q, the wider the range of β and the greater the contrast of enhancement. The larger the p, the larger the β, the more the reflection brightness is compressed, and the brighter the enhanced frame. In this paper, p is 0.25 and q is 0.1.

$$JND(l) = \begin{cases} 17 \times \left(1 - \sqrt{\frac{l}{127}}\right) + 3 & l \leq 127 \\ \frac{3}{128} \times (l - 127) + 3 & l > 127 \end{cases} \tag{8}$$

$$\beta(l) = p + \frac{q}{17} \times (20 - JND(l)) \tag{9}$$

Contrast Enhancement with LIPS. LIP, proposed by Jourlin [20], considers that light passes through a light intensity filter to form a transmitted light image that enters human eyes. In fact, the image is represented by an absorption filter function, which is defined as gray tone function f. For an 8-bit image I, its gray tone function is expressed as $f = M - I$ $(M = 256)$. Moreover, LIP model redefines addition, subtraction and scalar multiplication. Where, LIPS is denoted as Eq. (10), and $g = M - J$ is a gray tone function of image J.

$$f \ominus g = M \cdot \frac{f - g}{M - g} \tag{10}$$

In this paper, subtraction is used to improve the reflection brightness. Enhancement E is equivalent to reflection R' multiplied by luminance $M/(M - g)$ in (11). Analysis in (12–13) reveals that as g increases, brightness m_E and contrast σ_E^2 of reflection also increase. Where m_E and $m_{R'}$ are average brightness of enhancement and reflection; σ_E^2 and $\sigma_{R'}^2$ are the variance of enhancement and reflection, respectively.

$$E = M - f \ominus g = M - \frac{M - R' - g}{1 - \frac{g}{M}} = \frac{M}{M - g} \cdot R' \tag{11}$$

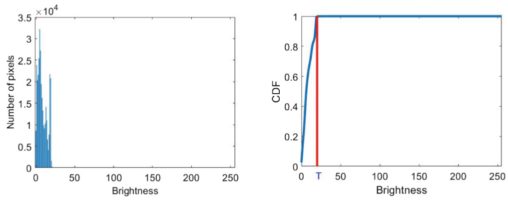
$$m_E = E\left(\frac{M}{M - g} \cdot R'\right) = \frac{M}{M - g} \cdot E(R') = \frac{M}{M - g} \cdot m_{R'} \tag{12}$$

$$\sigma_E^2 = E\left(\left(\frac{M \cdot R'}{M - g}\right)^2\right) - m_E^2 = \left(\frac{M}{M - g}\right)^2 \cdot \sigma_{R'}^2 \tag{13}$$

From Fig. 2(a) we know that pixels of reflection are mainly concentrated in a narrow brightness range. To maximize the brightness of enhanced frame without exceeding $[0, M)$, parameter g should select within $(0, M - R'_{\max})$. And the brightness and contrast are the maximum when g is $M - R'_{\max}$. However, maximum of reflection may deviate far from the brightness range of most pixels. Obviously, it is better to ignore those scattered bright spots in the reflection.

In Fig. 2(b), CDF grows sharply in $(0, T)$, while the flat portion exceeding T is scattered with a few bright spots. If an error e is set, the intensity T corresponding to CDF less than $1 - e$ could be taken as the maximum of reflection, that is $R'_{max} = T$. The value of e in this paper is $0.08\,\mu$, where μ is the average brightness of input frame. Next, calculate LIPS parameter according to (14). As a result, enhanced frame can be obtained by substituting (14) into (12).

$$g = M - R'_{\max} = M - T \tag{14}$$



(a)Brightness histogram (b)CDF

Fig. 2. Brightness histogram of reflection component and its CDF.

3.3 Inter-frame Brightness Continuity

Video scenes are complex and variable, independent enhancement of each frame ignores the correlation of adjacent frames. Especially for dynamic video with almost invariable or slowly changing background, the brightness continuity of adjacent frames should be guaranteed while improving brightness.

It is clear that frame enhancement in Sect. 3.2 is affected by two adaptive parameters (β and g). LIPS parameter g has a greater impact on final brightness. To ensure the inter-frame brightness continuity, we choose g of previous frame to enhance current frame for invariant or gradual scenes. Because one gray-level increase of g will cause the average brightness of enhanced frame to differ by several gray-levels when g is large. While frames with abrupt scene are enhanced by calculating g adaptively. In this section, the scene change is judged by calculating the motion pixel ratio in the background area with optical flow method.

Background Estimation. For a video with invariant or gradual background, the optical flow amplitude of the background is small, while the optical flow amplitude of foreground part is large. In order to estimate the background area more accurately, we record the part whose magnitude is greater than a threshold T_1 as the foreground by accumulating the optical flow (of) of P frames before current frame, and the rest is background area.

$$OF = \sum_{p=1}^{P} of_{t-p} \tag{15}$$

where t is the frame number of current frame. $t - p = max(C, t - p)$, and C is the first frame number of current scene. OF is the cumulative optical flow amplitude. In this paper, when $T_1 = 10$ and $P = 5$, estimated background is shown in Fig. 3.

Motion Pixel Statistics in the Background. In the previously estimated background region (Number of pixels is N_{bg}), the number of motion pixels (N_{of}) in current frame is counted, whose optical flow amplitude is greater than a

(a)One frame of a video sequence (b)Estimated background area

Fig. 3. Background area estimation. (Non-white area is the background.)

threshold T_2 in this region. When the background changes little with respect to previous frame, optical flow amplitude in the background larger than T_2 is less, and the proportion (N_{of}/N_{bg}) of moving pixels in the background is smaller.

In this paper, T_2 is set to 2 and the proportional threshold T_3 is set to 0.55. When the threshold T_3 is exceeded, it is considered that the background of current frame has a sudden change relative to the previous frame. Thus, parameter g of current frame should be recalculated and the frame number of current frame is record as the first frame of new scene ($C = t$).

Except for the frames with sudden scene change, those with brightness variation that is perceptible to human eyes but scene remains unchanged also need to re-estimated LIPS parameter g to prevent improper brightness enhancement. The brightness difference threshold T_4 of adjacent frames is calculated with (16), where μ_{t-1} is the previous frame's average brightness, and $JND(\mu_{t-1})$ is the visibility threshold. Brightness difference between adjacent frames greater than this threshold indicates that original video has a discontinuous brightness here. Parameter g should be updated. At the same time, the first frame of the new scene also needs to be updated, that is $C = t$. Finally, enhanced video is obtained by connecting the enhanced frame sequence into a video.

$$T_4 = JND(\mu_{t-1}) \tag{16}$$

4 Experimental Results and Analysis

All the experiments are carried out on a PC with 2.50 GHz CPU and 8G RAM. Performance of proposed method is compared with five algorithms including AGCWD [14], video enhancement proposed by Jiang [21], LIME [18], naturalness preserved image enhancement by Wang [12] and deep Retinex decomposition RetinexNet [22] in subjective and objective assessments. The first two are video enhancement algorithms, while the last three independently enhance each frame.

4.1 Subjective Assessment

Figure 4 presents one video sequence and its enhanced result using our method. It can be seen that video brightness is effectively improved. Nine frames with the size of 960 × 404 from three movie videos are shown in Fig. 5, which are the sequences that contain invariant, gradual and abrupt scenes. Horizontally, Jiang and Wang's algorithm, LIME and RetinexNet improve the brightness of each frame. However, over-saturation and noise amplification cause the frames unnatural. AGCWD increases the contrast, but bright areas are prone to overexposure and low contrast frame enhancement is insufficient. Our results are not as bright as those of other algorithms, but the details in bright area preserves well. As a result, enhanced frames look more natural. Vertically, whether the scene changes or not, our algorithm performs better for each frame.

4.2 Objective Assessment

This section selects one quality metric to evaluate enhanced frames, namely colorfulness-based patch-based contrast quality index CPCQI [24]. CPCQI calculates the perceived distortion, and value greater than 1 indicates quality enhancement, while the more it is less than 1, the more serious degradation is.

Table 1 shows the average CPCQI of three video sequences (100 frames of each video). It can be found that indexes of our method are ranked in the top one. And average CPCQI of ours is greater than 1, suggesting that frame quality is improved. While indexes of other algorithms are smaller than 1 in video 3, which means enhanced frame quality decreased. Especially the CPCQI of Jiang's algorithm and RetinexNet is smaller in three videos, indicating that the distortion is serious. AGCWD and Wang's algorithm improves the frame quality for video 1, 2, but failed in high contrast sequence (video 3). LIME produces distortion in video 1, 3, because it works better for very dark frames (video 2).

In addition, the average running speed of our method and five algorithms is also compared in Table 2. Except for RetinexNet with Python, other algorithms are processed by Matlab. Our algorithm ranked fourth in processing speed because bilateral filtering takes a long time. AGCWD and Jiang's algorithm and LIME process faster, while Wang's algorithm and RetinexNet process each frame independently at very slow speeds.

4.3 Flickering-Artifact Assessment

In order to visually demonstrate the brightness continuity, we compare the average brightness and flickering score of three videos. Their results are shown in Fig. 6. When the average brightness trend of enhanced video is consistent with that of original video and the average brightness difference between adjacent frames is not large, it is considered that no flicker occurs. Moreover, flickering score [11] defined in (17) is to evaluate the degree of brightness flicker.

$$FS = \frac{1}{M} \sum_{m=1}^{M} \frac{\left| \hat{f}_t(m) - \hat{f}_{t-1}(m) \right| + \alpha}{\left| f_t(m) - f_{t-1}(m) \right| + \alpha} \tag{17}$$

where f and $\hat{f}$ are frames before and after enhancement, and M is the number of blocks (4×4). Constant α is 1, $\|f_t(m) - f_{t-1}(m)\|_2^2 < \theta, \theta$ is 10. Flickering score close to 1 means that video is more flickering free.

In Fig. 6, from top to bottom are results of video sequence with invariant, gradual and abrupt scene respectively. For sequences with invariant or gradual scene in first two lines, brightness change of ours are consistent with original sequence, while AGCWD and Wang's algorithm produce noticeable brightness flicker. Other algorithms have no obvious brightness flicker in average brightness, but their flickering scores are higher due to the amplified noise. Sudden change of average brightness in the third line of Fig. 6(a) indicates that the scene changes, corresponding to the peak in flickering score. In Fig. 6(b), our algorithm has the lowest score in the first and third lines, suggesting no brightness flicker. Score in the second line is higher because of the noise, but there is still no flicker.

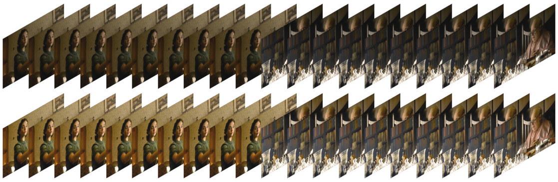


Fig. 4. Enhanced result of video sequence 3. (The first line is original video sequence and the second line is enhanced video sequence.)

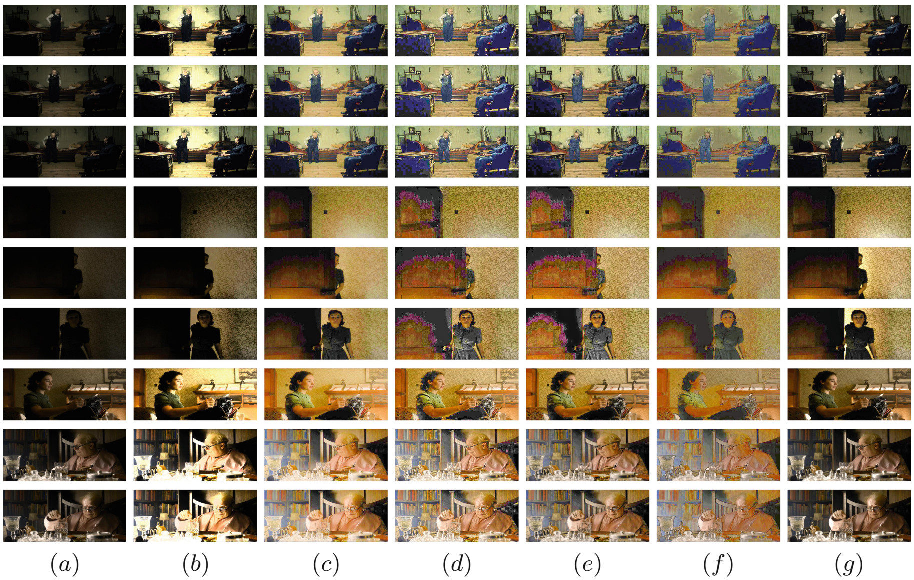


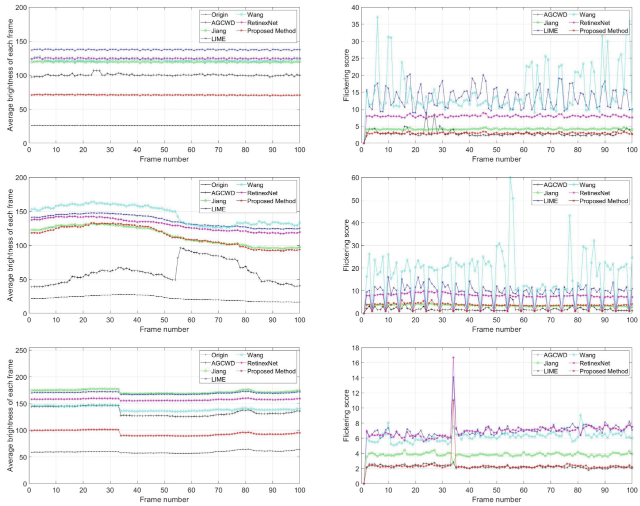
Fig. 5. Enhanced results of three videos. (Each three lines represent the first, middle and last frames of the video sequence. (a) Input frame, (b) AGCWD [14], (c) Jiang [21], (d) LIME [18], (e) Wang [12], (f) RetinexNet [22], (g) Proposed.)

Table 1. Average CPCQI of different algorithms for three enhanced video sequences.

Video	AGCWD [14]	Jiang [21]	LIME [18]	Wang [12]	RetinexNet [22]	Proposed
1	1.0134	0.9337	0.9954	1.0180	0.9339	**1.1093**
2	1.0324	0.9652	1.0428	1.0220	0.9487	**1.0535**
3	0.9225	0.7561	0.9163	0.9642	0.7984	**1.0528**

Table 2. Comparison of average running speed (frames/second).

	AGCWD [14]	Jiang [21]	LIME [18]	Wang [12]	RetinexNet [22]	Proposed
Speed	5.2713	0.7842	0.4926	0.0309	0.0735	0.3309



(a) Average brightness variation (b) Flickering score

Fig. 6. Comparison of brightness continuity for three videos.

5 Conclusion

In this paper, we propose an improved Retinex-based video enhancement algorithm. Weight factor is calculated to adjust illumination, so that reflection is compressed into a dark image with approximately uniform illumination. Then same LIPS parameter is adopted for frames with similar scene to ensure continuous brightness, while updated parameter for abrupt frames. Experiments show that our method has less distortion as well as no brightness flicker. Next, we'll focus on reducing processing time and adjusting LIPS parameter for gradual scene to improve the enhanced quality of frames farther from the first frame.

References

1. Pan, W., Gan, Z., Qi, L., Chen, C., Liu, F.: Efficient retinex-based low-light image enhancement through adaptive reflectance estimation and LIPS postprocessing. In: J-H, L., et al. (eds.) PRCV 2018. LNCS, vol. 11256, pp. 335–346. Springer, Cham (2018). https://doi.org/10.1007/978-3-030-03398-9_29
2. Chen, S.D., Ramli, A.R., Chiu, Y.S.: Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation. IEEE Trans. Consum. Electron. **49**(4), 1301–1309 (2003)
3. Stark, J.A.: Adaptive image contrast enhancement using generalizations of histogram equalization. IEEE Trans. Image Process. **9**(5), 889–896 (2000)
4. Gu, K., Zhai, G., Yang, X., Zhang, W., Chen, C.: Automatic contrast enhancement technology with saliency preservation. IEEE Trans. Circ. Syst. Video Technol. **25**(9), 1480–1494 (2015)
5. Jobson, D.J., Rahman, Z., Woodell, G.A.: Properties and performance of a center/surround retinex. IEEE Trans. Image Process. **6**(3), 451–462 (1997)
6. Rahman, Z., Jobson, D.J., Woodell, G.A.: Multiscale retinex for color rendition and dynamic range compression. In: Proceedings of SPIE, vol. 2847, pp. 183–191 (1996)
7. Jobson, D.J., Rahman, Z., Woodell, G.A.: A multiscale retinex for bridging the gap between color images and the human observation of scenes. IEEE Trans. Image Process. **6**(7), 965–976 (1997)
8. Kimmel, R., Elad, M., Shaked, D., Keshet, R., Sobel, I.: A variational framework for retinex. Int. J. Comput. Vis. **52**(1), 7–23 (2003)
9. Li, M., Liu, J., Yang, W., Sun, X., Guo, Z.: Structure-revealing low-light image enhancement via robust retinex model. IEEE Trans. Image Process. **27**(6), 2828–2841 (2018)
10. Xu, K., Jung, C.: Retinex-based perceptual contrast enhancement in images using luminance adaptation. In: 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1363–1367 (2017)
11. Yang, H., Park, J., Moon, Y.: Flickering effect reduction based on the modified transformation function for video contrast enhancement. IEIE Trans. Smart Process. Comput. **3**(6), 358–365 (2014)
12. Wang, S., Luo, G.: Naturalness preserved image enhancement using a priori multi-layer lightness statistics. IEEE Trans. Image Process. **27**(2), 938–948 (2018)
13. Dong, X., et al.: Fast efficient algorithm for enhancement of low lighting video. In: 2011 IEEE International Conference on Multimedia and Expo, pp. 1–6 (2011)
14. Huang, S.C., Cheng, F.C., Chiu, Y.S.: Efficient contrast enhancement using adaptive gamma correction with weighting distribution. IEEE Trans. Image Process. **22**(3), 1032–1041 (2013)
15. Ko, S., Yu, S., Kang, W., Kim, D., Paik, J.: Flicker-free low-light video enhancement using patch-similarity and adaptive accumulation. In: 2016 IEEE International Conference on Consumer Electronics (ICCE), pp. 215–216 (2016)
16. Ko, S., Yu, S., Kang, W., Park, C., Lee, S., Paik, J.: Artifact-free low-light video enhancement using temporal similarity and guide map. IEEE Trans. Ind. Electron. **64**(8), 6392–6401 (2017)
17. Land, E.H.: The retinex theory of color vision. Sci. Am. **237**(6), 108–129 (1977)
18. Guo, X., Li, Y., Ling, H.: LIME: low-light image enhancement via illumination map estimation. IEEE Trans. Image Process. **26**(2), 982–993 (2017)

19. Lucas, B., Kanade, T.: An iterative image registration technique with an application to stereo vision. In: Image Understanding Proceedings of a Workshop, vol. 81, pp. 121–130 (1981)
20. Jourlin, M., Pinoli, J.C.: A model for logarithmic image processing. J. Microsc. **149**(1), 21–35 (1988)
21. Jiang, X., Yao, H., Zhang, S., Lu, X., Zeng, W.: Night video enhancement using improved dark channel prior. In: 2013 IEEE International Conference on Image Processing, pp. 553–557 (2013)
22. Chen, W., Wang, W., Yang, W., Liu, J.: Deep retinex decomposition for low-light enhancement. In: British Machine Vision Conference (2018)
23. Jayant, N.: Signal compression: technology targets and research directions. IEEE J. Sel. Areas Commun. **10**(5), 796–818 (1992)
24. Gu, K., Tao, D., Qiao, J., Lin, W.: Learning a no-reference quality assessment model of enhanced images with big data. IEEE Trans. Neural Netw. Learn. Syst. **29**(4), 1301–1313 (2018)