A Novel Image Enhancement Method Based on Variational Retinex Approach

Jiaqing Hu\textsuperscript{1,3,a}, Hua Gao\textsuperscript{1,2,3,b,*}, Zhaosheng Zhang\textsuperscript{1,3,c}, Guoxi Lin\textsuperscript{1,d}, Hongyue Wang\textsuperscript{1,e}, Weijie Liu\textsuperscript{1,f}

\textsuperscript{1}Zhejiang Jieshang Vision Technology Co., Ltd, 998 Wenyi West Road, Yuhang District, 311121 Hangzhou City, China
\textsuperscript{2}College of Computer Science, Zhejiang University of Technology, 288 Liuhe Road, West Lake District, 310023 Hangzhou City, China
\textsuperscript{3}Collaborative Innovation Center for Economics Crime Investigation and Prevention Technology, Jiangxi Province, China

\textsuperscript{ajqhu@icarevision.cn, bghua@zjut.edu.cn, czszhang@icarevision.cn, dgxlin@icarevision.cn, ehongyuewang@icarevision.cn, fwjliu@icarevision.cn}

Abstract. Existing image enhancement methods, such as Retinex, only consider the spatial smoothness of the illumination image when dealing with low-contrast images in dark scenes, resulting in noise amplification and halation. In this paper, a novel image enhancement method based on variational framework is proposed, which effectively combines the advantages of MSRCR and variational approach. The method controls the selection of parameters under the variational framework by setting the brightness threshold of the image to ensure that the separated reflection image contain more detailed information. The illumination image is stretched by an adaptive contrast stretching method, and finally the reflected image is multiplied by the stretched illumination image to obtain the final enhanced image. Experiments on the images of night scenes show that our proposed algorithm effectively solves the halo phenomenon, reduces the noise and ensures the naturalness while enhancing the contrast.

1. Introduction
The image enhancement technology can improve the contrast of the original image and highlight the detailed information. The processed observation image is more in line with the visual characteristics of human eyes and is convenient for subsequent processing of other applications. The images obtained in daily life often have insufficient or uneven illumination, which seriously affects the observation quality of the images. Therefore, it is necessary to obtain images with better visual effects through image enhancement processing. Enhanced methods based on gradation transformation such as linear and non-linear stretching, log mapping, gamma correction, histogram equalization, etc. are simple and these methods are easy to implement and widely used for image enhancement. Due to the uneven illumination of the image, the image enhanced by the global grayscale transformation cannot improve the contrast of the detailed information. In order to adapt the non-uniform illumination image, some local adaptive methods are proposed. To prevent overexposure after histogram equalization, some restrictive algorithms such as brightness preservation [1, 2] and contrast limitation [3] have been proposed.
However, the enhancement methods based on the gray-scale transformation are all based on the pixel-to-pixel mapping and do not consider the spatial relationship between each other. Therefore, the pixels are stretched while the noise is also enhanced, and at the same time, the color information is distorted. Some scholars have found that inverted low-light images look like hazy images. Based on this finding [18, 19] is proposed to enhance the image by dehaze the inverted low-light images. Recently, with the rapid development of deep learning, some deep learning methods for enhancing low-contrast images [20, 21, 22, 23] have been proposed.

Land and McCann [4] proposed the Retinex theory based on the perceptual characteristics of the human visual system. Some scholars proposed different image enhancement methods based on the Retinex model. [5, 6, 7, 8, 9, 10], has achieved good results. The emphasis of these enhancement algorithms is mainly on how to effectively estimate the background illumination image. The center/surround Retinex algorithm [10, 11] is widely used due to its simplicity and speed. The center/surround Retinex uses Gaussian filtering to estimate the illumination image. Currently, the algorithms based on the center/surround Retinex mainly include SSR [12], MSR [13], and MSRCR [14]. The MSRCR method can compress the image dynamic range and effectively enhance the local contrast. However, the spatial smoothness of the reflection image is not taken into consideration, which easily leads to amplification of noise. In the process of color restoration, only the reflection image is considered, which easily leads to halo phenomenon at high contrast and destroys the naturalness of the image. The variational framework of the Retinex model [15] unifies the spatial smoothness of the illumination and reflects image into the objective function, which can suppress the noise and introduce the stretched illumination image during the color restoration process and so as to guarantee the naturalness of the restored image. However, when dealing with images of dark scenes, the variational approach has fewer details of the reflected image than the MSRCR. This is due to the variational approach limits the illumination propositions what not less than the observed image. However, the variational approach only employs gamma correction to stretch the illumination image during the color recovery phase. Due to the nature of the gamma curve, the brightness of the restored image is increased while the contrast is reduced.

Aiming at the above problems, we propose an improved method based on variational framework. This method adaptively selects parameters by judging the brightness of the input image. When the input image is dark, the weight of the corresponding disciplinary items is reset to zero. Removing the constraints of the illumination image is not less than the observed image, and degenerate into a center/surround Retinex to ensure that the obtained reflection component contains more information. Through the histogram distribution of the illumination image after gamma correction, the grayscale stretching parameters are set, the illumination image are stretched, and finally the stretched illumination image are multiplied with the reflection image to obtain the final enhanced image. Experiments show that this method effectively suppresses noise, eliminates halation, and ensures naturalness.

### 2. The variational Retinex approach

Retinex theory assumes that the original image \( S \) is the product of the illumination image \( L \) and the reflection image \( R \), \( S(x, y) = R(x, y) \cdot L(x, y) \). The purpose of image enhancement based on Retinex is to estimate \( L \) from \( S \), so as to decompose \( R \), eliminate the influence of light unevenness, and improve the visual effect of the image. In processing, each image is usually transferred to the logarithmic domain, ie \( s = \log S \), \( l = \log L \), \( r = \log R \), and so \( s = l + r \). Figure 1 shows the flowchart of the Retinex algorithm.

![Image](image.png)  
**Figure 1.** The flowchart of the Retinex algorithm.
The variational formulation for Retinex relies on the following assumptions:

1. The illumination is spatially smooth.
2. The reflectance image \( R \) is restricted to the unit interval \( (0 \leq R \leq 1) \), and therefore \( L \geq S \).
3. The illumination image is close to the input image \( S \), and enhancing the local contrast of the reflectance image \( R \).
4. The reflectance image \( R \) is spatially smooth.

Define \( s = \log S \), \( l = \log L \), \( r = \log R \). If we integrate all the above assumptions into one expression we get the following penalty functional:

\[
\text{Minimize: } F[l] = \int_{\Omega} \left( |\nabla| \alpha^2 + \beta |\nabla(l-s)|^2 \right) dx \, dy
\]

Subject to: \( l \geq s \)

Where \( \Omega \) indicates the effective area of the image. \( \alpha \) and \( \beta \) are free non-negative real parameters. In the functional \( F[l] \), The first penalty item \( |\nabla| \alpha^2 \) controls the spatial smoothness of illumination image. The second penalty item \( (l-s)^2 \) controls the illumination image close to the observed image. The third penalty term \( |\nabla(l-s)|^2 \) controls the spatial smoothness of reflection components.

The above minimization problem is solving a Quadratic Programming (QP) with unknown images. The Projected Normalized Steepest Descent (PNSD) method is used in the variational framework to iteratively obtain the optimal solution. And it is accelerated by the multi-scale resolution technique. Figure 2 shows the flowchart of the variational framework of Retinex.

\[\text{Figure 2. Returning part of the illumination to the reflectance image.}\]

The variational approach is very good when dealing with high brightness images, but the detail information of the separated reflection image is lost due to the constraint \( l \geq s \) when dealing with images in dark scenes. In the color recovery phase, it uses only gamma correction to stretch the illuminance image. Due to the nature of the gamma curve, the brightness of the recovered image is increased while the contrast is reduced. Figure 3 shows the enhancement effect of the variational approach on the image of different brightness.
3. The improved enhancement methods

This paper improves on the basis of traditional variational framework and proposes an effective image enhancement method. In this paper, the advantages and disadvantages of Retinex's variational framework and MSRCR method are compared by experiments. Adjusting the parameters adaptively according to the brightness of the input image. By analyzing the processing of MSRCR at the color recovery stage, a method for ensuring the naturalness of the image and eliminating the halation is obtained. The gamma correction function is analyzed and its limitations are obtained. On this basis, an adaptive grayscale stretching method is designed to enhance the illuminance image.

3.1. Adaptive adjustment parameters

Figure 4 shows the reflection components separated from the same dark scene image by the MSRCR method and variational framework. (a) is the original image, (b) is the reflection image of the MSRCR separation, (c) is the reflection of the separation of the variation. By comparing the extracted reflection image of the two, it can be clearly observed that the reflection image of the MSRCR retains more detailed information. This is a prerequisite for improving local contrast. However, there is a clear problem that the noise is enhanced and there is overexposure at the details.

The variational approach mentioned in the second section is finally transformed into the minimization problem of solving a Quadratic Programming. The objective function is as follows:

\[ \min F[l] = \int_\Omega \left( |\nabla l|^2 + \alpha (l - s)^2 + \beta |\nabla (l - s)|^2 \right) dx dy \]

Subject to: \( l \geq s \)
The necessary and sufficient conditions for its minimization are obtained via the Euler-Lagrange equations:

\[
\begin{aligned}
\left\{ \frac{\partial F}{\partial I} &= 0 = -\Delta l + \alpha(l-s) - \beta \Delta(l-s) \\
\text{and } l &> s \end{aligned}
\]  

(3)

Where \(\Delta\) indicates Laplace operator. The author uses the Projected Normalized Steepest Descent (PNSD) algorithm to solve the minimum of the quadratic objective function in the paper. The iterative form is as follows:

\[
l_j = l_{j-1} - \mu_{NSD} \cdot G
\]

(4)

Where \(l_j\) and \(l_{j-1}\) are the illumination images at step \(j\) and \(j-1\), respectively, \(G\) is the gradient of \(F[I]\), and \(\mu_{NSD}\) is the optimal line-search step size. The gradient of \(F[I]\) is given by:

\[
G = -\Delta l_{j-1} + (\alpha - \beta \Delta)(l_{j-1} - s)
\]

(5)

And \(\mu_{NSD}\) is given by:

\[
\mu_{NSD} = \frac{\int_{\Omega} |G|^2}{\int_{\Omega} (\alpha |G|^2 + (1+\beta)\nabla G |G|^2)}
\]

(6)

Observe that, by integration by parts, \(\int |\nabla G|^2 = -\int G \Delta G\) up to boundary conditions. Finally, projecting onto the constraint \(l \geq s\) is done by \(l_j = \max(l_j, s)\).

As author mentioned in the paper when setting \(\alpha = \beta = 0\) and removing the constraint of \(l \geq s\), we will get the process of homomorphic filtering and the variational framework degenerates into the center/surround Retinex method. Figure 4 shows that the reflection image separated by the MSRCR method contain more details. Therefore, in this paper, a link that can adjust the parameters adaptively according to the brightness of the input image is designed to switch between the variational approach and the MSR method, which ensures that the reflection image contains more detailed information.

We first calculate the average brightness of the input image to represent the lightness and darkness:

\[
T(x, y) = \max_{c \in \{r, g, b\}} I^c(x, y)
\]

(7)

\[
\text{mean} = \frac{1}{m \cdot n} \sum_{i=0}^{m} \sum_{j=0}^{n} T(i, j)
\]

(8)

Where \(I\) represents the input image, \(T\) represents the brightness image of \(I\), and \(\text{mean}\) is the average brightness of \(I\). In order to suppress the noise in the reflection image, we still set \(\beta = 0.1\) when dealing with dark scene images to ensure its spatial smoothness. We take the threshold \(t\), when \(\text{mean} \leq t\), set \(\alpha = 0\), \(\beta = 0.1\) and remove the constraint with \(l \geq s\). When \(\text{mean} > t\), set \(\alpha = 0.0001\), \(\beta = 0.1\) and make sure \(l \geq s\). Where \(\alpha = 0.0001\) and \(\beta = 0.1\) are the parameter settings given by the
author in his paper. The effect of different parameter values is shown in the figure below. The size of \( \beta \) controls the spatial smoothness of the restored image. The larger \( \beta \) is, the smoother the restored image is, the easier the local noise is suppressed, but the loss of detail information is more serious.

![Illustration](image.png)

**Figure 5.** The influence of \( \beta \): Constant \( \beta = 0 \) in (a), \( \beta = 0.1 \) in (b), and \( \beta = 10 \) in (c).

We generate a series of images of different brightness through multiple images of different scenes with better visual effects. The series of images are enhanced by MSRCR and variational approach respectively, and the enhanced images and the original images are calculated by SSIM. The statistical results are shown in Figure 6. From the statistical line graph, it can be found that the MSRCR (blue line) is better than the variational approach (red line) when the average brightness of the image is less than 32, and the variational approach is superior to the MSRCR when the average brightness is greater than 32. According to statistical analysis, we take the threshold \( t = 32 \), the green line in the figure shows the SSIM indicator of our method.

![Graph](image.png)

**Figure 6.** Comparison of SSIM between MSRCR and Variational Retinex.
Figure 7 shows the reflection images separated by the traditional and improved variational approach. It can be seen that the reflection image has obtained more detailed information by the improved method so as to suppress noise, prevents overexposure.

![Figure 7. The reflectance image of the variational Retinex and after the improvement.](image)

3.2. Color recovery

After obtaining the reflection component, we are faced with how to restore enhanced image that conforms to human visual characteristics. The separated illuminance image preserves the natural information of the observed image [16, 17]. Without the illuminance image, the reflection image is directly stretched and it is easy to cause the restored image to lose its naturalness, such as MSRCR. Another benefit of using color components for color recovery is that it effectively suppresses the halo phenomenon. The reason why the halo can be suppressed is that the strong change in the reflection image is complementarily canceled in the illuminance image.

In the variational approach, the illumination image is stretched only by gamma correction resulting in a darkened image, which is related to the characteristics of the Gamma curve while increasing the brightness causes the local contrast to be compressed. According to \( U_{out} = (V_{in} / 255)^{1/\gamma} \cdot 255 \), we draw the \( \gamma = 2.2 \) and \( \gamma = 5.0 \) curves respectively, as shown in Figure 6. From the graph we can find the curves of \( \gamma = 2.2 \) and \( \gamma = 5.0 \) are respectively cut to the parallel lines \( V_{out} = V_{in} \) at \( t1 \) and \( t2 \). The \( \gamma = 5.0 \) curve only stretches the gray level from 0 to \( \gamma 2 \), but the gray level from \( \gamma 2 \) to 255 are compressed. Despite improving the overall brightness, it compresses more detailed information.

![Figure 8. The curves of \( \gamma = 2.2 \) and \( \gamma = 5.0 \).](image)
Aiming at the limitation of Gamma curve, this paper proposes an adaptive grayscale stretching method to enhance the illumination image of dark scenes. We choose a piecewise function to perform the stretching. Its expression is as follows:

\[
U_{\text{out}} = \begin{cases} 
(u / v) \cdot V_{\text{in}} & (0 \leq \text{value} < v) \\
(255 - u) / (255 - v) \cdot V_{\text{in}} + u & (v \leq \text{value} \leq 255)
\end{cases}
\]  

(9)

We need to determine \(u\) and \(v\) in the formula above. First, we perform a gamma correction of \(\gamma = 1.2\) on the isolated illumination image. Then, the histogram of the enhanced illumination image is counted as shown in Figure 7(a). We obtain \(v\) by ensuring that the number of pixels between gray scale 0 and \(v\) accounts for 0.98 of the total number of pixels. To prevent overexposure, we choose \(u = 220\). Finally, we get the piecewise function, as shown in Figure 9(b). It can be seen that the piecewise function stretches the pixels between gray levels 0 to \(v\) containing the main information of the illumination image, and at the same time, the brightness is greatly increased. Figure 10 shows the restoration effect of a dark scene image. (a) is a directly separated illumination image. (b) is the illumination image by gamma correction with \(\gamma = 2.2\). (c) is the illumination image after stretching by the method of this paper.

Figure 9. The histogram distribution of illumination image and the piecewise function.

Figure 10. Illumination image after different stretching methods.

Figure 11 shows a flowchart of the method of this paper. The main steps of the method are as follows:

1. Get the brightness of the input image to find the average brightness \(\text{mean}\).

\[
\begin{align*}
\gamma & = 1.2 \\
u & = 220 \\
v & = \text{value accounts for 0.98 of the total number of pixels}
\end{align*}
\]
(2) Adjust parameter by comparing with threshold.
(3) Turn the input image into the logarithmic domain. Use the parameters set in step (1) to determine the illumination image $I$. Turn back to time domain $L$, and separate the reflection image $R$.
(4) Enhancing the illumination image $L$ using an adaptive grayscale stretching method. Finally, multiply the reflection image $R$ and the enhanced illumination image $L$ to obtain an enhanced image $S'$.

Figure 11. The flow chart of the improved method.

4. Experiments and analysis
In order to verify the validity of the method proposed in this paper, some comparative experiments were performed with MSRCR and traditional variational approach respectively. Figure 12 shows the halo suppression effect, (a) is the original, (b) is the effect of MSRCR, (c) is the effect of the method of this paper. It can be seen from Figure 10 that the halo is well suppressed. The reason why the halo can be suppressed is the strong changes in the reflection image are complementarily canceled in the illumination image.

Figure 12. Halo effect comparison.

Figure 13 shows the comparison between our method and the MSRCR and variational methods for recovering different images. From the effect of recovery, we can observe that our method effectively enhances the contrast of low-quality images, and suppresses the noise better. The restored image does not have obvious halo, and the overall tone is more in line with the real scene, ensuring the nature.
Based on the MSE and PSNR indicators, we made quantitative comparisons of different algorithms. The comparison results are shown in Figure 14. The smaller value of MSE means the better denoising effect, while the larger value of PSNR and SNR represent the better denoising effect. From the analysis in the figure, we can see that our proposed algorithm performs better on noise suppression.
5. Conclusion
This paper proposes an improved image enhancement method based on variational framework of Retinex. Adjusting the weight parameters of each item in the objective function according to the intensity of the input image. When entering a dark scene image, we remove the constraint of \( I \geq s \) so that the separated reflection image contains more information. In the color recovery phase, the adaptive grayscale stretching method is used to enhance the illumination image, which compensates for the limitations of the gamma curve stretching, thereby enhancing the brightness and contrast of the final enhanced image.

Acknowledgements
Supported by the Opening Project of Collaborative Innovation Center for Economics Crime Investigation and Prevention Technology, Jiangxi Province (No. JXJZXTCX-016), and Natural Science Foundation of Zhejiang Province (No. LGG18F030003).

References
[1] C. Wang and Z. Ye, “Brightness preserving histogram equalization with maximum entropy: A variational perspective,” IEEE Trans. Consum. Electron., vol. 51, no. 4, pp. 1326–1334, Nov. 2005.
[2] H. Ibrahim and N. Kong, “Brightness preserving dynamic histogram equalization for image contrast enhancement,” IEEE Trans. Consum. Electron., vol. 53, no. 4, pp. 1752 – 1758, Nov. 2007.
[3] A. M. Reza, “Realization of the contrast limited adaptive histogram equalization (CLAHE) for real-time image enhancement,” J. VLSI Signal Process., vol. 38, no. 1, pp. 35 – 44, 2004.
[4] E. Land and J. McCann, “Lightness and retinex theory,” Journal of the Optical society of America, vol.61, no.1, pp.1–11, 1971.
[5] H. Ngo, M. Zhang, L. Tao, and V. Asari, “Design of a digital architecture for real-time video enhancement based on illumiance-reflectance model,” Midwest Symposium on Circuits and Systems, vol.1, no.1, pp.286 – 290, 2006.
[6] E. Provenzi, M. Fierro, A. Rizzi, L.D. Carli, D. Gadia, and D. Marini, “Random spray retinex: a new retinex implementation to investigate the local properties of the model,” IEEE Transactions on Image Processing, vol.16, no.1, pp.162 – 171, 2006.
[7] J. Morel, A. Petro, and C. Sbert, “A pde formalization of retinex theory,” IEEE Transactions on Image Processing, vol.19, no.11, pp.2825 – 2837, 2010.
[8] G. Lyu, H. Huang, H. Yin, S. Luo, and X. Jiang, “A novel visual perception enhancement algorithm for high-speed railway in the low light condition,” IEEE 12th International Conference on Signal Processing, pp.1022 – 1025, 2014.
[9] Y. Lu, F. Xie, Y. Wu, Z. Jiang, and R. Meng, “No reference uneven illumination assessment for dermoscopy images,” IEEE Signal Processing Letters, vol.22, no.5, pp.534–538, 2014.
[10] A. Grigoryan, S. Agaian, and A. Gonzales, “Fast fourier transform-based retinex and alpharooting color image enhancement,” SPIE Sensing Technology and Applications. International Society for Optics and Photonics, pp.94970X–94970X–12, 2015.
[11] D. Jobson, Z. u. Rahman, and G. Woodell, “A multiscale retinex for bridging the gap between color images and the human observation of scenes,” IEEE Transactions on Image Processing, vol.6, no.7, pp.965–976, 1997.
[12] D. Jobson, Z.-U. Rahman, and G. A. Woodell, “Properties and performance of a center/surround Retinex,” IEEE Trans. Image Process., vol. 6, no. 3, pp. 451–462, Mar. 1997.
[13] D. J. Jobson, Z.-U. Rahman, and G. A. Woodell, “A multiscale Retinex for bridging the gap between color images and the human observation of scenes,” IEEE Trans. Image Process., vol. 6, no. 7, pp. 965 – 976, Jul. 1997.
[14] Z.-U. Rahman, D. J. Jobson, and G. A. Woodell, “Retinex processing for automatic image enhancement,” J. Electron. Imag., vol. 13, no. 1, pp. 100–110, 2004.
[15] R. Kimmel, M. Elad, D. Shaked, R. Keshet, and I. Sobel, “A variational framework for Retinex,” Int. J. Comput. Vis., vol. 52, no. 1, pp. 7–23, 2003.

[16] Wang S, Zheng J, Hu H M, et al. Naturalness preserved enhancement algorithm for non-uniform illumination images [J]. IEEE Transactions on Image Processing A Publication of the IEEE Signal Processing Society, 2013, 22 (9): 3538.

[17] Fu X, Liao Y, Zeng D, et al. A Probabilistic Method for Image Enhancement With Simultaneous Illumination and Reflectance Estimation[J]. IEEE Transactions on Image Processing A Publication of the IEEE Signal Processing Society, 2015, 24 (12): 4965.

[18] X. Dong, G. Wang, Y. Pang, W. Li, J. Wen, W. Meng, and Y. Lu, “Fast efficient algorithm for enhancement of low lighting video,” in Proceedings of IEEE Conference on Multimedia & Expo (ICME), pp. 1–6, 2011.

[19] Galdran A, Alvarez-Gila A, Bria A, et al. On the Duality Between Retinex and Image Dehazing [J]. 2017.

[20] Dong C, Chen C L, He K, et al. Image Super-Resolution Using Deep Convolutional Networks [J]. IEEE Trans Pattern Anal Mach Intell, 2016, 38 (2) :295 - 307.

[21] Lore K G, Akintayo A, Sarkar S. LLNet: A deep autoencoder approach to natural low-light image enhancement [J]. Pattern Recognition, 2016, 61:650 - 662.

[22] Shen L, Yue Z, Feng F, et al. MSR-net:Low-light Image Enhancement Using Deep Convolutional Network [J]. 2017.

[23] Divakar N, Babu R V. Image Denoising via CNNs: An Adversarial Approach [C]// Computer Vision and Pattern Recognition Workshops. IEEE, 2017: 1076 - 1083.