Color image enhancement based on adaptive multi-scale morphological unsharpening filter

X LIU1,2, X H XIA1,2, L WANG1,3, J H CAO1

1 Key Laboratory of Metallurgical Equipment and Control Technology, Wuhan University of Science and Technology, Ministry of Education, Wuhan 430081, China
2 Engineering training Centre, Wuhan University of Science and Technology, Wuhan 430065, China
3 Center for Service Science and Engineering, Wuhan University of Science and Technology, Wuhan 430065, China

Abstract. In order to overcome the problem in Retinex algorithm that it is possible to cause image detail loss by using Gauss function to estimate illumination, in this paper, we propose a color image enhancement algorithm based on multi-scale morphology unsharp method combined with Retinex. Firstly, the color image is converted from RGB space to HSV space. Then, the S component is enhanced by adaptive logarithmic transformation to improve its visual characteristics and make it consistent with human visual system. The method of multi-scale morphological unsharpening is adopted to estimate the V component, and the multi-scale weights are adaptively selected according to the features of the image. The V component is enhanced according to the Retinex principle. Finally, the H and the enhanced S and V components are recombined and reflected into RGB space to achieve the purpose of image enhancement. The experimental results showed that the algorithm is superior to the traditional SSR, MSR and MSRCR algorithms in terms of entropy, average gradient and sharpness, and outperforms those based on Gauss function estimation.

1. Introduction

Under the influence of environmental illumination, photographed images often have low illumination levels and the blurred parts of interested areas, which increase the difficulty of automatic recognition of computers. In order to facilitate the subsequent advanced processing, we need to enhance the images to improve the performance of image recognition. Image enhancement technologies can improve the image contrast, adjust its dynamic range, highlight the areas of interest and improve the use value of images. Therefore, it is widely used in many fields such as image processing and intelligent recognition system.

Histogram equalization is a classic image enhancement algorithm, and it can be divided into global or local histogram equalization for different applications. The basic idea of image enhancement algorithm transform domain is to map the signal from space domain to the transform domain, and to enhance it in the transform domain. Finally, the image is restored to the space domain by inverse transform. Wavelet transform, non-subsampling contourlet transform and other multi-resolution analysis tools are commonly used in such algorithms. Multi-resolution analysis is helpful to enhance the general picture while preserving the details in the image, but with the increase of transformation layer number, the computation amount of the algorithm will increase significantly. Retinex is an image enhancement algorithm based on human vision system with the characteristics of dynamic range.
compression and color constancy. It is compatible with the nonlinear characteristics of human vision, and can achieve better enhancement effect. Thus, it has been widely concerned by researchers in recent years. Single scale Retinex (SSR) and multi scale Retinex (MSR) are two kinds of widely used algorithms. However, when there are multiple light sources in an image, SSR algorithm is easy to generate halation in the image. MSR is a linear superposition of multiple SSR, which can suppress halation generation to a certain extent, and also improve brightness and contrast in images. But this superposition may also cause some color distortions in images, and the edges and details of the images will also be blurred. Multi scale Retinex with color restoration (MSRCR) improves the color distortion of MSR, but it will increase the overall brightness of the image.

From the existing literature on image enhancement using Retinex algorithm, scholars mainly used the Gaussian filter to estimate the incident light component, and then subtract the estimated value from the image, resulting in the reflection component. However, the Gauss filter not only inhibits the intensity of the incident light, but also blurs the edge details in the original image, making this part of the information lost, which is the deficiency of the Retinex model. Ma et al. applied the total variation regularization constraint to Retinex, and achieved good results, but partial information loss still exists. On the basis of the Retinex principle, in this study the image is firstly transformed from RGB space to HSV space. The improved morphological unsharpening filter is used to replace the Gauss filter in the estimation of the incident light component for V component, which improves the edge details in the image. To prevent color distortion in the enhanced image, a piecewise logarithmic transformation of the S component in the original image is carried out, so as to improve the distribution of S components to adapt to the human eye's visual characteristics. Finally, the enhanced V, S and H components are re-transformed to RGB space to realize image quality improvement. Experimental comparison showed that the new algorithm has good performance in enhancing image quality and preserving image detail information. The structure of this paper is as follows. First, the basic principle of Rentinex and mathematical morphology is introduced. Then the image enhancement algorithm based on the above principle is introduced. The third part includes the experiment and data comparison analysis. Finally, the conclusion of the study is given.

2. Basic principle of Retinex and morphological image processing

2.1 Principle of Retinex

The human eye perception of object brightness is made up of two parts, namely, the illuminance part (E) from the external environment and the reflection part from the object surface to human eyes (R). The color characteristics of the external world perceived by human beings are mainly from the reflection part, as expressed by (1), in which (1b) is the result of logarithm for (1a).

\[ I(x, y) = E(x, y) \cdot R(x, y) \]  
\[ \log(I(x, y)) = \log(E(x, y)) + \log(R(x, y)) \]  

The basic idea of Retinex is to estimate \( E(x, y) \) by \( I(x, y) \), and subtract the estimated value from \( I(x, y) \), resulting in the estimation of \( R(x, y) \), as expressed by (2).

\[ \log(R(x, y)) = \log(I(x, y)) - \log(\hat{E}(x, y)) = \log(I(x, y)) - \log(F(x, y) \cdot I(x, y)) \]  

where \( \hat{E}(x, y) \) is the estimation of illumination component \( E(x, y) \), which mainly distributes in low frequency band since environmental illumination usually changes slow. Ciurea et al. used the center / surround Gaussian filter to estimate the illumination component, i.e., \( F(x, y) \) in (2), as expressed by (3), where \( \sigma \) is the scale parameter for the Gaussian surround function, and \( \lambda \) is a constant, such that meet (4).

\[ F(x, y) = \lambda e^{-((x^2+y^2)/2\sigma^2)} \]  

\[
\iint F(x, y) \, dx \, dy = 1
\]  

(4)

2.2 Basic principle of morphology

Morphology is a discipline based on mathematical set theory. Its basic idea is to regard images as a set. It uses a probe called structuring element, and detects the related shape information and the relationship between the shape information and probes in an image, and extract the global or local features of the image. In essence, morphological processing is a nonlinear filtering of images. In morphology, two basic operations are defined – dilation and corrosion, as shown in Figs. 5(a) and 5(b), respectively, where \( f \) is the image to be processed, and \( b \) is the structure element.

\[
[f \oplus b](x, y) = \max\{f(x-u, y-v)\}
\]  

(5a)

\[
[f \Theta b](x, y) = \min\{f(x+u, y+v)\}
\]  

(5b)

Based on the calculation of dilation and corrosion, two operations of opening and closing are defined, which are given by (6a) and (6b) respectively. Opening operation can filter out the bright features less than the structural elements in the original image, while closing operation can filter out the dark features less than the structural elements in the original image.

\[
(f \circ b)(x, y) = (f \Theta b) \oplus b
\]  

(6a)

\[
(f \bullet b)(x, y) = (f \oplus b) \Theta b
\]  

(6b)

Based on opening and closing operations, two operations of top-hat and bottom-hat operations are defined and given by (7a) and (7b). Top-hat transform can extract the bright features less than the structural elements in the original image, while bottom-hat transform can extract the dark features of the original image less than the structural elements.

\[
TH(x, y) = f(x, y) - (f \circ b)(x, y)
\]  

(7a)

\[
BH(x, y) = f(x, y) \bullet b(x, y) - f(x, y)
\]  

(7b)

3. Retinex image enhancement algorithm based on morphology

The proposed image enhancement algorithm is shown in Fig. 1. Since HSV color space is more consistent with the visual habits of human eyes, and the tone information in the HSV space is contained in the H component, by adjusting the V and S components and maintaining the H component, the visual features of the image can be enhanced and the color of the original image will not be distorted. First, the image to be enhanced is transformed from RGB space to HSV space, and the three components of H, S and V are separated. For the V component, it contains the brightness information in the original image, the illumination component is estimated by the improved morphological unsharpening filter, and then the Retinex algorithm is used to obtain the enhanced V component. For S component, adaptive logarithmic transformation enhancement algorithm is used to improve the dynamic distribution of saturation components. Finally, the enhanced V and S components are combined with the original H component, and then mapped to RGB space through color space transformation to obtain the enhanced image.
3.1 Saturation component enhancement algorithm based on adaptive logarithmic transformation

Saturation reflects the brightness of color. When the saturation is high, the color will be too bright; conversely, if the saturation is low, the color will be dim. Therefore, the principle of enhancing S component is that lower saturation should be properly stretched and higher saturation should be properly compressed, in order to keep the dynamic range of saturation in the right position. The logarithmic function in homomorphic filtering has better visual characteristics and accords with the above principle of saturation enhancement.

Saturation is adjusted within a smaller range, i.e., $S(x, y) \approx S'(x, y)$, where $S'(x, y)$ is the adjusted saturation. Considering $\lim_{y \to 0} \ln(x + 1) \sim x$, the form of the logarithmic transformation function can be selected as $\ln(x + 1)$. Let $\mu_S$ and $\sigma_S$ be the mean and variance of the normalized S component, respectively. Take $\mu_S \pm \sigma_S$ as the segmented endpoint, for saturation of $S < \mu_S - \sigma_S$, proper stretching should be made, while for saturation of $S > \mu_S + \sigma_S$, proper compression is needed. Therefore, the form of adaptive logarithmic transformation function for saturation can be expressed in (8)

$$S'(i, j) = \begin{cases} \frac{\mu_S - \sigma_S}{\ln(\mu_s - \sigma_s + 1)} \cdot \ln(S(i, j) + 1) & S(i, j) < \mu_S - \sigma_S \\ S(i, j) & \mu_S - \sigma_S \leq S(i, j) \leq \mu_S + \sigma_S \\ \frac{\mu_S + \sigma_S}{\ln(\mu_s + \sigma_s + 1)} \cdot \ln(S(i, j) + 1) & S(i, j) > \mu_S + \sigma_S \end{cases}$$

where the coefficients are determined by the mean and variance of the S component in the original image. The degree of stretching or compression can be adjusted adaptively according to the degree of S deviating from the mean value. Meanwhile, it also ensures that the saturation adjustment function will not mutate at the boundary point which causes color distortion.

3.2 Value component enhancement algorithm based on improved morphology unsharpening filter with Retinex
Unsharpening filtering\textsuperscript{17} can enhance the edge details of an image, which overcomes the shortcoming of using the center surround Gaussian filter in Retinex algorithm. The process of unsharpening can be expressed as

\[ g(x, y) = f(x, y) + K[f(x, y) - T(x, y)] \quad (9) \]

where \( f(x, y), g(x, y), \) and \( T(x, y) \) represent the original image, the processed image and the low pass filtered image of the original image, respectively. \( K \) is a constant coefficient for controlling the sharpening effect. Introducing morphological operators into the unsharpening filter results in (10).

\[ g(x, y) = f(x, y) + K\left( \sum_{i=1}^{N} \lambda_{oi}D_{oi} - \sum_{i=1}^{N} \lambda_{ci}D_{ci} \right) \quad (10) \]

where

- the meanings of \( f(x, y), g(x, y) \) and \( K \) are the same as those in (9);
- \( D_{oi} \) is the top-hat transform on each scale (as shown in (7a));
- \( D_{ci} \) is the bottom-hat transform on each scale (as shown in (7b));
- \( \lambda_{oi} \) and \( \lambda_{ci} \) are the weights of top-hat and bottom-hat transform on each scale.

According to the principle of top-hat and bottom-hat transform, the weights are adaptively improved. It can be known from the basic principles of top-hat and bottom-hat transform that \( D_{oi} \) extracts the bright features of the original image smaller than the structural element at this scale, while \( D_{ci} \) extracts the dark features. Firstly, the V component of the original image is normalized. Let \( \mu_v, \sigma_v \) be the mean and the variance of the V component of the original image, respectively. \( \mu_{v, i} \) and \( \mu_{v, i}^{*} \) are the mean of the opened and the closed images of the original image at the i-th scale. If \( \mu_v < 0.5 - \sigma_v \), the overall brightness of the original image is dark. At this point, the bright features can be moderately stretched, and the dark features can be compressed. Conversely, if \( \mu_v > 0.5 + \sigma_v \), bright features can be compressed while dark features can be stretched. Based on this idea, the values of \( \lambda_{oi} \) and \( \lambda_{ci} \) can be expressed by (11) and (12), respectively.

\[ \lambda_{oi} = \begin{cases} \frac{1 + (\mu_v - \mu_{v, i})}{\sum_{i=1}^{N}[1 + (\mu_v - \mu_{v, i})]} & \mu_v < 0.5 - \sigma_v \\ \frac{1 - (\mu_v - \mu_{v, i})}{\sum_{i=1}^{N}[1 - (\mu_v - \mu_{v, i})]} & \mu_v > 0.5 + \sigma_v \end{cases} \quad (11) \]

\[ \lambda_{ci} = \begin{cases} \frac{1 - (\mu_{v, i} - \mu_v)}{\sum_{i=1}^{N}[1 - (\mu_{v, i} - \mu_v)]} & \mu_v < 0.5 - \sigma_v \\ \frac{1 + (\mu_{v, i} - \mu_v)}{\sum_{i=1}^{N}[1 + (\mu_{v, i} - \mu_v)]} & \mu_v > 0.5 + \sigma_v \end{cases} \quad (12) \]

In (11), since morphological opening operation can filter out bright features less than structural elements, with the increasing of the scale of structural elements, the corresponding weights increase.
This can not only stretch bright features, but also restrain the excessive edge sharpening caused by small scale structural elements. Meanwhile, in order to prevent the value range from exceeding 1 after stretching, the weights of all scales are normalized. The meanings of the terms in (12) are similar to (11). Then, according to (2), we can obtain the improved expression of the enhancement algorithm, as expressed by (13), where $\alpha_i$ are the weights on each scale.

$$\log(R(x, y)) = \sum_{i=1}^{N} \alpha_i [\log(I(x, y) - \log(g(x, y))]$$

(13)

3.3 Algorithm steps

Step 1: Transform the color image from RGB space to HSV space and separate the three components of H, S and V;

Step 2: Calculate mean $\mu_S$ and variance $\sigma_S$ of S component, and enhance the S component according to (8);

Step 3: The structural elements B and scale N are selected, with the structural elements on each scale being $NB = B \oplus B \oplus \ldots \oplus B$ $N-1$ Times;

Step 4: Normalize the V component and calculate the normalized mean $\mu_V$ and variance $\sigma_V$. Then, use the structural elements on all scales to open and close V components, and calculate $\mu_{V^{*}}$ and $\mu_{V^{*}}$.

Step 5: Substitute $\lambda_{\mu}$ and $\lambda_{\sigma}$ according to (11), (12).

Step 5: Substitute $\lambda_{\mu}$, $\lambda_{\sigma}$ and (7a), (7b) into (10) to calculate $g(x, y)$. For convenience, set $K=1$. Then substitute $g(x, y)$ into (13) to calculate enhance V component;

Step 6: Combine H and enhanced S and V components, and transform it back to RGB space, resulting in the enhanced color image.

4. Experiments and data analysis

In order to verify the effectiveness of the proposed method, we designed the following experimental contents and compared the proposed method with commonly used Retinex algorithms. The experimental environment in this study is as follows. Software platform: MATLAB, version 2014; hardware platform: Core i5 processor with 4GB memory. For the reason of space, three groups of experimental results were selected as shown in Figs. 2 ~ 4.
Fig. 2 Football test images.

(a) Original image          (b) Proposed       (c) SSR
(d) MSR                                      (e) MSRCR

Fig. 3 Girl test images.

(a) Original image         (b) Proposed        (c) SSR
(d) MSR                                        (e) MSRCR

Fig. 4 Hall test images.

(a) Original image         (b) Proposed        (c) SSR
(d) MSR                                      (e) MSRCR
By comparing Figs. 2~4, it can be found that the image after SSR and MSR enhancement is relatively bright, due to the excessive brightness adjustment. Moreover, the phenomenon of color distortion appears in the processed images of SSR and MSR algorithm. MSRCR algorithm has improved compared with SSR and MSR on this two points, but the details of the image are blurred, and some details are missing. The proposed algorithm has much improvement in preserving image detail information than MSRCR, which can be seen from the surface particles of rugby and blue fabric in Fig. 2, the girl's hair and the car in the distance in Fig. 3 and the texture of walls and floor tiles in Fig. 4. Besides, the algorithm is superior to the other three algorithms in enhancing the image sharpness, which can be seen from the letters on rugby in Fig. 2, the mirror of girls in window glass Fig. 3, and the human and light background in Fig. 4.

In order to evaluate the superiority of the proposed algorithm more objectively, three quantitative indices, including image entropy, image average gradient and image clarity, were selected to compare the algorithms of this paper and SSR, MSR and MSRCR algorithms. The quantitative evaluation results of several algorithms are listed in Table 1. The greater the value of these quantitative indicators is, the better the algorithm is.

| Image name | Comparison object | Image entropy | Avg gradient | Clarity |
|------------|-------------------|---------------|--------------|---------|
| football   | Original image    | 6.7551        | 0.044823     | 38.047  |
|            | SSR               | 7.0479        | 0.075164     | 30.264  |
|            | MSR               | 7.1765        | 0.093660     | 37.711  |
|            | MSRCR             | 7.1315        | 0.06315      | 25.427  |
|            | Proposed          | 7.2077        | 0.10165      | **40.648** |
|            | Original image    | 7.1773        | 0.01101      | 12.595  |
|            | SSR               | 7.0248        | 0.01205      | 13.785  |
|            | MSR               | 7.0918        | 0.01646      | 22.264  |
|            | MSRCR             | 7.1402        | 0.00649      | 10.859  |
|            | Proposed          | 7.1939        | **0.01950**  | **22.300** |
|            | Original image    | 5.1995        | 0.01175      | 9.1525  |
|            | SSR               | 5.2407        | 0.01425      | 11.095  |
|            | MSR               | 5.3614        | 0.01612      | 15.343  |
|            | MSRCR             | 5.4256        | 0.01742      | 13.564  |
|            | Proposed          | 5.4381        | **0.01991**  | **15.501** |

The calculation methods of image entropy, image mean gradient and image clarity are respectively given by (14) ~ (16), respectively.

\[
H(x) = -\sum_{x \in L} p(x) \log p(x)
\]  

\[
\bar{G} = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \left( \frac{(I(i,j) - I(i+1,j))^2 + (I(i,j) - I(i,j+1))^2}{2} \right)
\]  

\[
Q = \sqrt{RF^2 + CF^2}
\]

\[
RF = \frac{1}{M(N-1)} \sum_{i=1}^{M} \sum_{j=1}^{N-1} (I(i,j) - I(i,j+1))^2
\]

\[
CF = \frac{1}{(M-1)N} \sum_{i=1}^{M-1} \sum_{j=1}^{N} (I(i+1,j) - I(i,j))^2
\]  

(14)  

(15)  

(16)
5. Conclusions
To deal with the problem of color image enhancement, a color image enhancement algorithm was proposed in this study. The adaptive logarithmic transformation was used to enhance the saturation of the image and adjust its dynamic range, so that its distribution will be more consistent with human visual characteristics. The improved multi-scale morphological unsharpening algorithm was used to replace Gauss center/surround filter, which can preserve the edge details in enhanced images. The experimental results demonstrated that the proposed color image enhancement algorithm is superior to the Gauss center/surround filter based Retinex algorithm in entropy, average gradient, clarity, etc.

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