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Adaptive Image Enhancement Method Based on Gamma Correction

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Abstract: *To address the problems of local detail loss and sharpness degradation in traditional image enhancement algorithms under low illumination conditions, an image enhancement algorithm based on the Weber-Fechner law is proposed. The adaptive gamma correction function and the adaptive contrast enhancement function are used to reduce the noise interference of the original image, the RGB mode of the original image is converted to HSV mode to improve the overall visual comfort of the image, the classical adaptive correction algorithm is optimised to separate the luminance components into blocks and obtain two images; Finally, the image fusion technique is used to extract the details from the two images and synthesise the final image. The images enhanced are clearer, brighter and more natural than the classical algorithms.*

Keywords: *Adaptive image enhancement; low illumination image; Multiscale*

1. Introduction

In the acquisition and processing of digital images, the quality of digital images can be degraded by light sources, angles, atmospheric quality, image transmission noise and other factors. Especially under low illumination conditions, digital images not only suffer from colour distortion and loss of detail, but can even affect the user's recognition of key image information [1]. Image enhancement is a key aspect of digital image processing. Through noise reduction and enhancement processing of digital images, detailed features in the image can be highlighted. Research on enhancement algorithms for digital images under low illumination conditions mainly includes histogram equalisation algorithms SSR image enhancement algorithms [2], and fuzzy set-based image enhancement algorithms. The histogram equalisation algorithm enhances the contrast of the whole image by improving the grey level range of the digital image, which is simple and effective, but this enhancement algorithm is not effective for image edge and local detail processing.

The overall structure of this paper is as follows: Section 2 briefly describes the work on low-light image enhancement. Section 3 describes the key steps of the method proposed in this paper. In Section 4, experimental results are analysed and conclusions are presented in Section 5.

2. Related work

There are two traditional low-illumination image enhancement algorithms, the grey scale transformation method and the histogram equalisation method [3]. Kim et al [4] enhance the contrast of images by a block iterative histogram method and use a moving template to perform partial overlap sub-block histogram equalisation (POSHE) on individual parts of the image. This is known as adaptive histogram homogenisation, or AHE for short. Celik and Tjahjadi [5] proposed the Context and Variance Contrast (CVC) enhancement algorithm, which uses the 2D of the input image and a contextual information model for non-linear data mapping to achieve low illumination image enhancement.

With the development of machine learning, the technique has also been used in recent years for image enhancement. Lore et al [6] developed a deep learning-based self-encoder method using sparse denoising autoencoders in a low-illumination image enhancement framework. This algorithm still does not handle well the over-enhancement caused by uneven image illumination.

3. Our method

The original RGB image is processed in one of two alternative ways. The first processing method is

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the adaptive contrast enhancement function. The second processing method is to process the rgb image using an adaptive gamma correction function. Afterwards, the RGB image that has been processed is converted to HSV colour space and the V component is extracted. Then, the parameter values of the adaptive enhancement function are adjusted with respect to the light distribution to obtain two images. Next, some information about the image is obtained by using image fusion techniques, and this information can be used to enhance the V-component. Finally, the image is converted from HSV space back to RGB space and the final adjusted image is output. The whole process is shown in the Fig.1

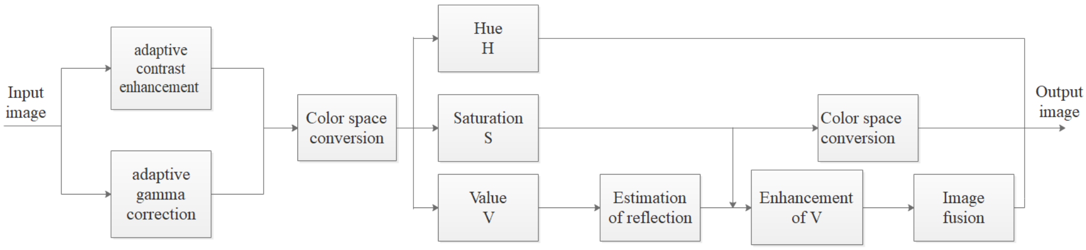


Figure 1: Framework of the proposed algorithm

3.1. Adapative functions

3.1.1. Adapative contrast enhancement function

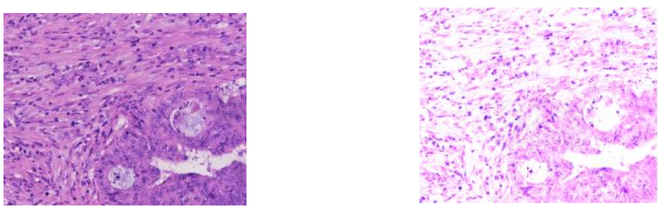
A very well-known algorithm for local contrast enhancement is Adaptive Contrast Enhancement (ACE), which uses an inverse sharpening mask technique. Firstly, the input image is divided into two parts. One is the low-frequency unsharp mask component, which can be obtained by low-pass filtering (smoothing, blurring techniques) of the image. The second is the high-frequency component, which can be obtained by subtracting the unsharp mask from the original image. The contrast gain is calculated as follows.

$$\mathrm{f(i,j)} = \mathrm{m_x(i,j)} + \mathrm{G(i,j)[x(i,j)} - \mathrm{m_x(i,j)]} \tag{1}$$

The function G(i,j) is the contrast gain and f(i,j) indicates the corresponding enhanced pixel value of x(i,j) denotes the local area and the equation is as follows.

$$\mathrm{m_x(i,j)} = \frac{1}{(2n+1)^2}\sum_{k=i-n}^{i+n}\sum_{l=i-n}^{j+n}\mathrm{x(k,l)} \tag{2}$$

The effect of ACE is shown in Fig.2.



(a) Source image *(b)*

Figure 2: Effect of adapative contrast enhancement function

3.1.2. Adapative gamma correction function

The algorithm has the function of adapting to the pixel intensity and enhancing the local contrast of the image. Average of brightness is simple element that can be computed in the least amount of time. Assuming that a reasonable image should have a mean value of all pixels (after normalisation) of 0.5, the gamma value for automatic gamma correction should be such that the target image moves towards this target. Assuming that X is the mean value of the image, the formula for the mean value of the image required for automatic gamma correction is as follows. And the effect of adapative gamma correction is shown in Fig.3.

$$X^r = 0.5 \tag{3}$$

$$\mathrm{r} = \log_X \frac{1}{2} \tag{4}$$

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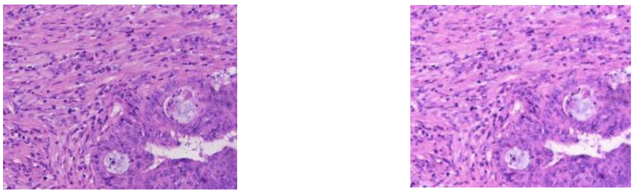


(a) Source image *(b)*

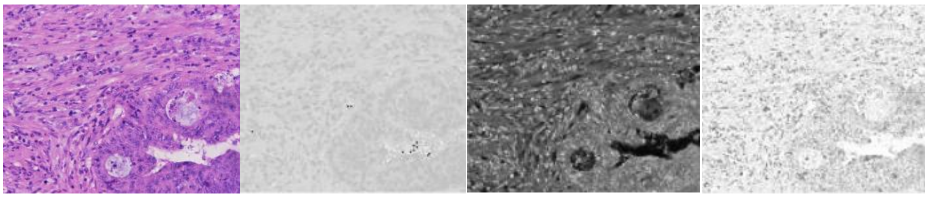
Figure 3: Effect ofadapative gamma correction

3.2. Space conversion

The human eye responds more strongly to luminance than to colour [7]. Correction of the light component is therefore essential for algorithms that aim to correct images with uneven lighting conditions. Due to colour images, it is difficult to ensure that all channels are enhanced or attenuated if the correction is applied directly to the red (R), green (G) and blue (B) channels. The channels are enhanced or attenuated in the appropriate proportions, which often leads to colour distortion in the image after correction processing. Corrective processing often results in colour distortion of the image. Given that the HSV colour space is better suited to the visual properties of the human eye and that the hue (H), saturation (S) and luminance (V) in the colour space are independent of each other, the manipulation of the luminance component V does not affect the quality of the image. The manipulation of the components does not affect the colour information of the image. Therefore, after pre-processing the image, the colour image will be corrected in HSV space. The mathematical expression of the conversion from RGB space to HSV space is as follows:

$$\begin{cases} V = max(R,G,B) \\ S = 1 - min(R,G,B)/V \\ H = \begin{cases} 60x(G-B)/(V-min(R,G,B)) & if\ V = R \\ 120 + 60x(B-R)/(V-min(R,G,B)) & if\ V = G \\ 240 + 60x(R-G)/(V-min(R,G,B) & if\ V = B \end{cases} \end{cases} \tag{5}$$

The equation are the red, green and blue channels in the RGB colour space, and H, S and V are the hue, saturation and luminance channels in the HSV colour space. After conversion from RGB space to HSV space, sub-images Ih (x, y), Is (x, y) and Iv (x, y) are obtained corresponding to each component value (H, S, V), as shown in Figure 4.



(a) Source image *(b) Hue* *(c) Saturation* *(d) luminance*

Figure 4: Example of the conversion from RGB space to HSV space

3.3. Estimation of the reflection component

The multiscale Gaussian function method is effective in compressing the dynamic range and accurately estimating the lighting components in a scene. The Gaussian function is calculated as follows:

$$G(x,y)=\gamma e^{-\frac{x^2+y^2}{\sigma^2}} \tag{6}$$

$\gamma$is the scale parameter and satisfies the following conditions: $\iint G(x,y)dxdy = 1$. Convolution of the image using a Gaussian function gives an estimate of the value for the illuminance component. The results are shown below.

$$I_{v\_g}(x, y) = I_v(x, y) *G(x, y) \tag{7}$$

Where Iv(x, y) is the input image and Iv_g(x, y) is an estimate of the illumination component. The expressions are as follows.

$$I_{v\_g}(x, y) =\sum_{i=1}^{N} \theta_i I_v(x, y) *G_i(x, y) \tag{8}$$

θ_i is the weighting factor of the light component with i scales extracted from the Gaussian function, N is the number of scales used. To extract the values of the light components, this article uses N = 3.

3.4. Adaptive brightness enhancement

In order to increase the illuminance value in the under-illuminated areas, an adaptive luminance correction method will be used. According to the Weber-Fechner law, when light reflected from an object hits the retina, the optic nerve responds to the light, and this response is the subjective perceived luminance that can be received by the human eye. The luminance of light reflected from an object is called the objective luminance I_v, while the luminance perceived by the human eye is called the subjective luminance perception I_v. Their relationship is as follows.

$$I'_v = \frac{I_v(255+k)}{I_v+k} \tag{9}$$

The value 255 is the grey level of the 8-bit image and k is the adjustment factor,with the adjustment range decreasing as the k value increases. The enhancement formula is as follows.

$$I'_v = \frac{I_v(255+k)}{(\max(I_{v,}I_{v\_g}))+k} \tag{10}$$

I_v is the enhanced image, I_v is the image before enhancement, and I_{v_g} is the reflection component estimated from I_v. In the experiment, K was obtained from the average of the saturation component image Is as follows:

$$k = \alpha \times \frac{1}{W}\sum_{i=1}^{W} I_s \tag{11}$$

α is the weighting factor, and W is the total number of pixels in the image I_s.

3.5. Image fusion

Image fusion techniques can effectively extract image features and fuse key features of sub-images. Fusion algorithms obtain the fused image by calculating the weighted additive of the source image.

$$F = \sum_{i=1}^{N} \omega_i S_i \tag{12}$$

F is the fused image, S_i is the source image to be fused, and ω_i is the weighting factor. The process is shown in Figure 5.

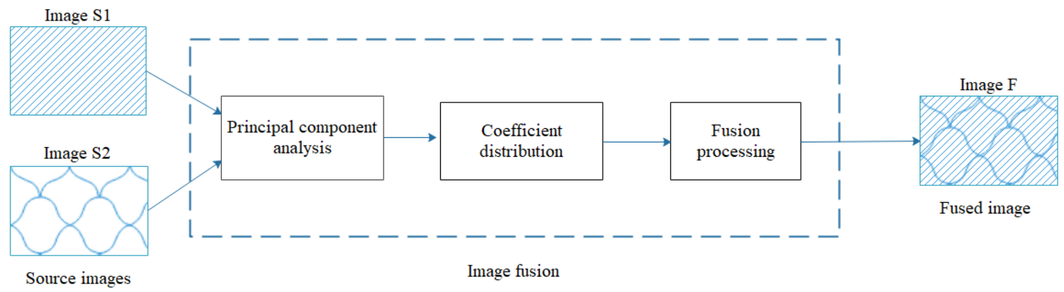


Figure 5: Image fusion process based on PCA transformation.

3.6. Converting to RGB space

The image is converted to RGB space using the formula.

4. Experiment and analysis

This paper uses code running on MATLAB 2020a to verify the effectiveness of the algorithm. The experimental images all have large differences in brightness. Some of the experimental results are shown in Figure 6. The three sets of experimental images are named 'dusk' and 'castle'.

In the following, the experimental images will be processed by several leading image enhancement algorithms in order to assess the effectiveness of the algorithms. The following section will assess the quality of the output images in terms of visual evaluatio, objective quantitative analysis and the

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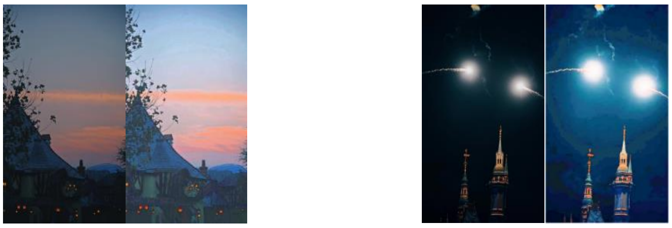
enhancement under extreme conditions.



(a) 'dusk' *(b) 'castle'*

Figure 6: Part of the experimental results

4.1. Visual evaluation

(1) Comparison with traditional image enhancement algorithms

Figure7 shows the experimental results of image enhancement after processing the original image with the proposed algorithm and several conventional algorithms. Figure 7(a) shows the original image, while Figures 7(b)-(e) show the processing results of histogram equalisation, contrast limited adaptive histogram equalization, index transformation and the algorithm proposed in this paper. As shown, the method proposed in this paper significantly improves colour and detail and outperforms the other algorithms in terms of visual effect.

(a) Source image *(b) HE* *(c) CLAHE* *(d) index* *(e) our method*

Figure 7: Comparison of the proposed algorithm with several conventional algorithms.

4.2. Objective quantitative analysis

In this paper, the effectiveness of the chosen algorithm is assessed by information entropy and the average gradient [7].

(1) Information entropy: Source symbol set{A} is defined as the set of all possible symbols {ai}, and the probability of source symbol {ai} is P(ai).

$$H = -\sum_{i=1}^{L} P(a_i)\log_2 P(a_i) \tag{13}$$

(2) Average gradient: The AG reflects the ability to express the details of an image and can be used to measure the relative clarity of the image.

$$AG = \frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\sqrt{\frac{(\partial f/\partial x)^2+(\partial f/\partial y)^2}{2}} \tag{14}$$

Where M and N are the width and height of the image, respectively, $\partial f/\partial x$ represents the horizontal gradient, and $\partial f/\partial y$ represents the vertical gradient.

4.3. Image enhancement under extreme conditions

Images with very low luminance were also used to evaluate the proposed algorithm. The experimental results are shown in Figure 8. The original image is in the first row.

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(a) image 1 *(b) image 2* *(c) image 3* *(d) image 4*

Figure 8: Examples of the original images used in the experiment

Table 1: The IE of the images

	Original	HE	CLAHE	Index	Our
image1	6.70	7.88	7.27	5.28	7.45
image2	5.55	6.56	6.32	5.46	7.34
image3	7.31	7.88	7.55	5.16	7.92
image4	5.89	7.26	6.86	5.21	7.63

Table 2: The AG of the images

	Original	HE	CLAHE	Index	Our
image1	1.95	3.39	6.09	3.66	4.85
image2	4.4	6.24	7.12	5.63	5.54
image3	2.66	4.03	4.89	3.33	5.81
image4	2.38	4.25	5.12	5.58	6.86

5. Conclusion

Based on the light reflection model and multi-scale theory, this paper proposes a non-linear transformed image correction method for the problem of inhomogeneous illumination and the lack of adaptability of image enhancement algorithms. The proposed algorithm balances the colours of the image better than the classical algorithm, has better detail retention, and can uncover details that were missed in the original image due to poor contrast, which greatly improves the image quality.

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